Student Award Paper in the
54th meeting of Acoustic Emission Working Group (AEWG), Princeton, NJ, USA, May 21-22, 2012

Introducing Sifted *b*-Value Analysis and a New Crack Classification for Monitoring Reinforced Concrete Shear Walls by Acoustic Emission

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INTRODUCTION

The damage of Reinforced Concrete (RC) shear walls as the main gravity and lateral force resisting systems is a major problem for engineers. Failure of a shear wall may sometimes deal with homeland security if they happen in nuclear power plants or concrete bridges in crowded metropolises. Acoustic emission (AE) technique has shown promising progress in recent decades. However, lack of research on AE monitoring of RC shear walls is recognizable in literature. Among various methods in AE parametric evaluation, *b*-value is being used to demonstrate the condition of a concrete specimen [1]. Typically, *b*-value increases during the nucleation of micro-cracks, become quite constant when micro-cracks merge to localize macro-cracks, and decreases when the macrocracks begin to open [2]. However, existence of lots of fluctuation in the *b*-value trend due to reflections, huge amount of cracks, reinforcing bars, attenuation, unloading, etc. lead to difficulties in executive decision making. This issue is aggravated when a large specimen is subjected to a reversed cyclic loading where the scattering effect is large and hits from loading and unloading alter *b*-value trend on and on. Systematic crack mode classification incorporated with *b*-value analysis can also be used as an indicator on the status of damage in shear or tensile crack mode. The problem in classical crack classification based on rise time, amplitude, duration and ring-down count is the proportionality of tensile to shear cracks [3]. This paper addresses these two problems by making advantage of statistical tools, Gaussian smoothing on *b*-values and k-mean clustering. These approaches are exploited to introduce a “Sifted *b*-value (S*b*)” analysis in which after appropriate feature extraction of signals, they will be screened by statistical k-mean clustering and then will be send to *b*-value analysis. The S*b*-value analysis can report the damage statues of both crack modes and predict failure mechanism to clarify required retrofitting procedure.

TEST SETUP

The test specimens were two large scale RC shear walls, SW1 and SW2, with the thickness of 0.2m and a height to width ratio of 0.94 and 0.54, respectively [4]. Figure 1 shows the experimental setup and dimensions along with AE instrumentation. The in plane quasi-static reversed cyclic loading protocol consisted of 10 load steps (LS) starting from LS1 to LS10 for SW1 and 10 load steps starting from LS2 to LS11 for SW2. Each load step consists of two cycles. The force-displacement hysteresis loops and their corresponding backbone in Figure 2 show that SW1 reached its maximum capacity at LS9 and onset of nonlinearity was LS7 while in SW2 these features had occurred in LS10 and LS8, respectively [4],[5]. The main components of the AE system included an eight-channel high-speed data acquisition board (Physical Acoustics Corporation Micro-II PAC) and AEwin software for signal processing and recording. SW1 was instrumented with eight R15α AE sensors and SW2 with four R15α and four R6α. These piezoelectric resonance transducers transform transient elastic waves to electric waveforms which are digitized and stored by AE system. The sensors were attached to one face of the wall using hot glue. Preamplifiers were set at 40 dB gain and analog bandpass filters were adjusted in the interval of 20 kHz to 400 kHz. Trigger levels of 35 dB and 48 dB were respectively selected for SW1 and SW2 to remove background noise in the day of test.

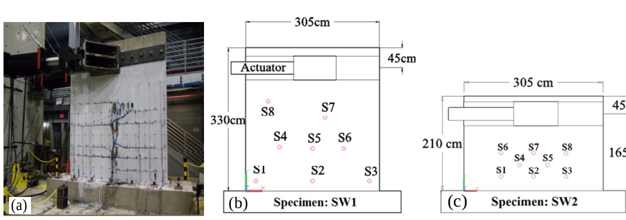

Figure 1. Test setup, specimens dimension, instrumentation and sensor layout: (a) Laboratory setup (b) SW1 (c) SW2

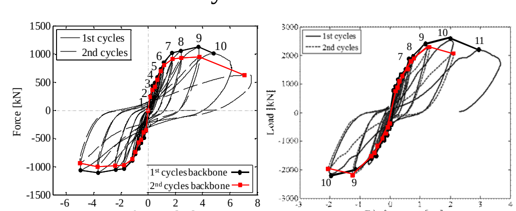

Figure 2. Hysteresis loops for (a) SW1 (b) SW2

GAUSSIAN FILTERING ON *B*-VALUE AND RESULTS

The *b*-value is obtained using the frequency–magnitude distribution data by means of Gutenberg–Richter

relationship, which is generally used in seismology. The Gutenberg–Richter formula in terms of AE technique is as follow:

$$\log N = a - b(A_{dB}/20) \qquad \text{(Eq. 1)}$$

where N is the incremental frequency (i.e. the number of AE events with amplitude greater than the threshold), a is an empirical constant, b is the b-value, and A_{dB} is the peak amplitude of AE event in decibel. Groups of 70 hits were selected to start the analysis. Based on the highly fluctuated result of b-value, no decision could be possibly make. A typical solution is uniform moving average but in order to keep the local b-value drop during loadings, our proposed workaround is the Gaussian smoothing. Gaussian functions have the following properties that make them particularly useful in smoothing filters [6]: (1) The Gaussian function is symmetric about the mean, and the weights assigned to signal values decrease gradually with distance from the mean. (2) The width of the Gaussian function is determined by its spread parameter, i.e., the standard deviation. As the standard deviation decreases, Gaussian function does less smoothing. Conversely as the spread parameter increases, the amount of smoothing is increased. (3) The local extrema (e.g. b-value drop) observed at one standard deviation are also observable at the smaller standard deviations and no more local extrema are created as the spread parameter increases. Gaussian smoothing is literally the convolution of a Gaussian window and a 1-D vector of data. The Gaussian smoothing $F(x)$ of a 1-Dimentional signal, $f(x)$, is defined as:

$$F(x) = f(x) * g(x,\sigma) = \int_{-\infty}^{\infty} f(\mu) g(x-\mu,\sigma) d\mu = \int_{-\infty}^{\infty} f(\mu) \frac{1}{\sqrt{2\pi}\sigma} exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right] d\mu \qquad \text{(Eq. 2)}$$

where "*" denotes convolution with respect to x, $g(x,\sigma)$ is the Gaussian function with the standard deviation σ, and μ is a dummy variable. These filtering parameters in addition to window span should be properly selected to clarify the trend. The results of raw b-value and smoothed b-value are illustrated in Figure 3 and Figure 4. These results confirm that micro-cracks were growing prior to LS3 and were localized to form macro-crack prior to LS5. From this load step onward, the macro-cracks opening is observed that was in good accordance with visual inspection.

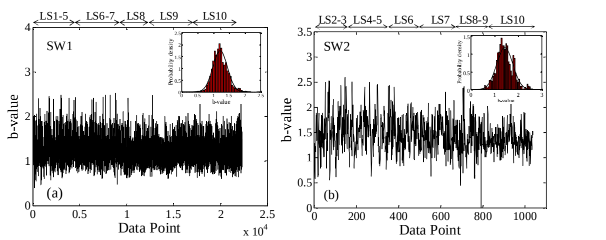

Figure 3. Raw b-values before being processed (a) SW1; (b) SW2

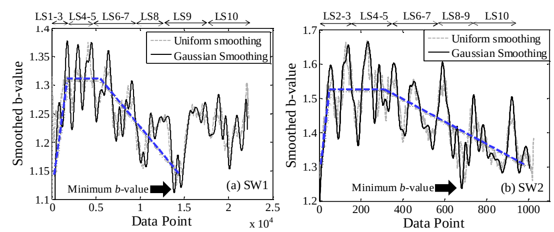

Figure 4. Smoothed b-values for: (a) SW1 (b) SW2

NEW CRACK CLASSIFICATION AND RESULTS

Crack classification based on Japan Construction Material Standards JCMS-IIIB5706 [7] employs two parameters of the Average Frequency and the RA value as follow:

RA = (Rise time) / (Peak Amplitude) (Eq. 3)
Average Frequency = (AE ring-down count) / Duration (Eq. 4)

Rise time, peak amplitude, and duration in Eq. 3 and Eq. 4 are depicted in Figure 5a. In this figure, ring-down count is shown by solid circles in intersection of threshold and AE signal. Cracks will be categorized as Figure 5b illustrates. However, a defined criterion (the inclined line) on the proportion of the RA value and the average frequency for crack classification has not been confirmed [3]. In the present work, the widely-used k-means pattern recognition method is utilized to classify the AE events in two dominant shear and tensile groups. This method aims at partitioning the data sets into k disjoint subsets (clusters) based on minimizing the summation of square distance of each data point in a subset to the center of the subset in which it is partitioned [8]. Indeed, several studies based on pattern recognition of AE events have determined that it is feasible to distinguish efficiently the events associated with various failure mechanisms. Suppose that a data set $\mathbf{X}=\{x_1, x_2, \ldots, x_N\}$, $x_n \in R^d$, is available. k-means aims at partitioning this data sets into k disjoint subsets, $C_1, \ldots, C_k$, through minimizing the criterion or clustering error as follow [8]:

$$E(m_1, m_2, \ldots, m_k) = \sum_{i=1}^{N} \sum_{j=1}^{k} I(x_i \in C_j) \left\| x_i - m_j \right\|^2 \qquad \text{(Eq. 5)}$$

where m_j is the center of j^{th} cluster, C_j, and $I(P)$=1 if P is true and 0 otherwise. This criterion can be minimized

through iterative procedure summarized in the following steps: (1) Initializing k centers,$\{m_1,\ldots, m_k\}$, through randomly dividing the data set into k groups and calculating the mean value for each subset. (2) Assigning each data point, x_n, to a cluster, C_j , that its center, m_j, has the lowest Euclidean distance to the point among other cluster centers. (3) Re-computing the centers for k clusters, $\{m_1,\ldots, m_k\}$. (4) If the change in centers in two proceeding steps is less than a certain threshold then algorithm is converged and terminate the iteration; otherwise go to step 2.

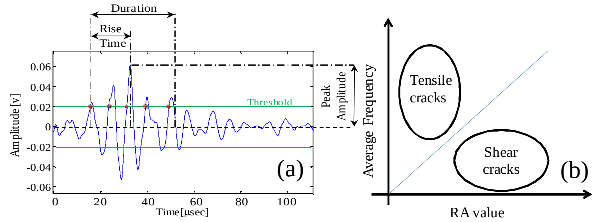

Figure 5. (a) AE parameters in an AE signal, (b) Signal Classification [7]

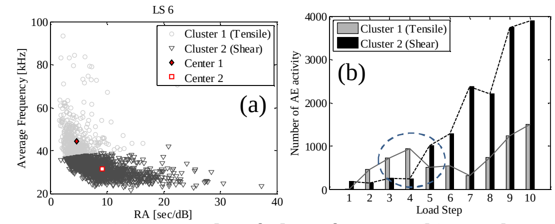

Figure 6. (a) example of classification (b) number of AE hits associated to tensile or shear mode

The systematic crack classification is done on SW1 that both modes were visibly occurred. The result of k-mean clustering and an example plot that shows how these cracks are classified at LS6 of SW1 are manifested in Figure 6. The dominancy of tensile cracks in the initial load steps and superiority of shear mode cracks from LS5 onward is evident is this figure. The length of tensile and shear mode cracks in each mode verify the outcomes. Finalizing the process by performing sifted b-value analysis lead to having knowledge about each crack mode, see Figure 7. The criticality of tensile cracks due to their monotonic reduction is elaborated in the results of S*b*-value analysis. To verify this prediction, SW1 was pulled toward complete collapse. Figure 8 proves the flexural (tensile) failure mode.

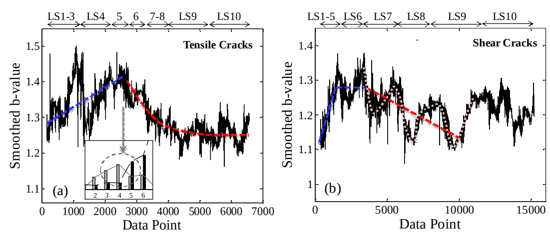

Figure 7. Sifted *b*-value analysis results: (a) Tensile cracks (b) Shear cracks

Figure 8. Tensile mode as the failure mode of SW1 in LS11, monotonic pulling to collapse

CONCLUSION

Reinforce concrete shear walls are among large structural elements that their acoustic emission monitoring is not straightforward due to large scattering effect. Gaussian smoothing is a powerful filter for clarifying the trend of b-value in order to monitor the transition of micro-cracks to macro-cracks. To monitor the majority of a crack mode in a shear wall, new crack classification based on k-mean analysis on RA and AF parameters resulted in promising outcomes. Sifted *b*-value (S*b*) analysis can reveal the severity of damage in each crack mode to predict the failure mechanism and helps to select appropriate retrofitting scenario.

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